Sustainable Systems Research

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Overall Review

- Center for Advanced Infrastructure and Transportation (CAIT) – annual funding over $12M
- Our team –
  - 9 Ph.D. students
  - 2.5 full time staff (programmers)
  - Contractors
  - Annual funding ~ $1M
  - Areas of research:
    - Energy systems, building, communities, industrial processes
    - Transportation - safety, mobility and energy
  - Funding sources: DOD, DOT, DOE, CEC, FHWA, Siemens, DNV-KEMA, internal

Research Areas

Time **Short Term (15min-24h)** **Long Term (months, years)**

Scale

Individual Building

Load forecasting and Control
- Physics + statistics based energy forecasts
- Real-time MPC control
- Day-ahead planning optimization
- Real-time load tracking control

iBEAM
- HVAC system degradation, O&M
- Building value model

cBEAM
- Common resources, budget constraints, O&M

Building Cluster/ Industrial Complexes/ Communities

Demand/Generation management
- Dynamic pricing & coordinated response
- Microgrid control (day ahead and same day)
- Energy Efficiency & MPC
- Storage control

Microgrid Planning and investment
Net Zero communities
AFV fueling infrastructure

Load forecasting and Control

Real Building

Simulation Model

Forecast Model ("Hybrid")

Use simulation data at the beginning to build model **offline**

Use real/trending data to update model **online**

Weather
(temperature, humidity,...)

Operations
(light, plugs, occupancy, ...)

Controls
(setpoints, day-night mode, ...)

Consumption

Temperature

Load forecasting and Control

Objective: Building a prediction model to capture the complex dynamics of the thermal and operational behavior in the building

- Energy-Plus but with minimum number of runs
- Data Driven Models i.e. statistical models/ Neural Network

offline

online

Objective: Developing Building Optimal Control Strategy

- Use real-time sensor data
- Grey-box model (physical/ statistical model)
- **MPC** - to minimize the energy cost while keeping comfort

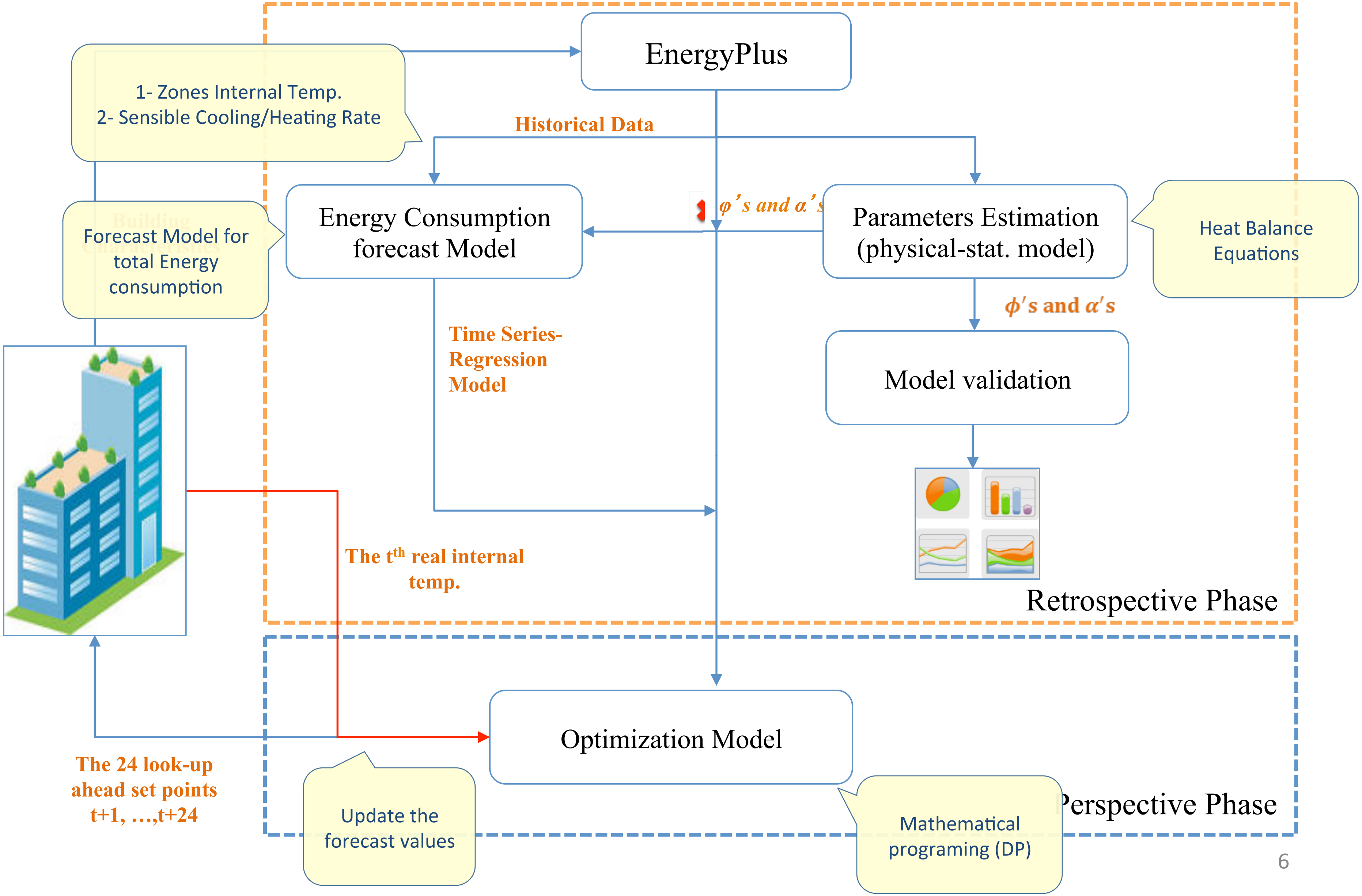
Objective: Load Planning and Load Tracking

- Use real-time sensor data
- Black-box model (Neural Network)
- **Load planning** – to minimize energy cost
  Load tracking – to track the consumption commitment made in day-ahead planning

Industrial processes and complexes

Residential/commercial complexes

Physical-Statistical Model



Physical-Statistical Model – Parameter Estimation

effective power rate

$$T_{in}^{t+1}(i) = T_{in}^{t}(i) + \alpha_i . R^t(i) + \varphi_i \left(T_{in}^{t}(i) - T_{ext}^{t}(i)\right) + \varepsilon^t$$

1

i_{th} zone

Estimated Using the Least Square Error Technique

Effect of other parameters + random effect

$$Q_i = \sum_{t=1}^{N} \left(T_{in}^{t+1}(i) - \hat{T}_{in}^{t+1}(i)\right)^2$$

$$\frac{\partial Q_i}{\partial \alpha_i} = 0 \qquad \boxed{\hat{\alpha}_i = \frac{\sum_{i=1}^{N} R^t(i).\Delta T_i^t \sum_{i=1}^{N} (\Delta\tau_i^t)^2 - \sum_{i=1}^{N} \Delta T_i^t.\Delta\tau_i^t \sum_{i=1}^{N} \Delta T_i^t.R^t(i)}{\sum_{i=1}^{N} R^t(i)^2 \sum_{i=1}^{N} (\tau_i^t)^2 - \sum_{i=1}^{N} (R^t(i).\Delta\tau_i^t)^2}}$$

$$\frac{\partial Q_i}{\partial \varphi_i} = 0 \qquad \boxed{\hat{\varphi}_i = \frac{\sum_{i=1}^{N} \Delta T_i^t.\Delta\tau_i^t \sum_{i=1}^{N} R^t(i)^2 - \sum_{i=1}^{N} \Delta T_i^t.R^t(i) \sum_{i=1}^{N} \Delta\tau_i^t.R^t(i)}{\sum_{i=1}^{N} R^t(i)^2 \sum_{i=1}^{N} (\tau_i^t)^2 - \sum_{i=1}^{N} (R^t(i).\tau_i^t)^2}}$$

1) Rogers, A., Maleki, S., Ghosh, S., and Jennings, N. R. Adaptive Home Heating Control Through Gaussian Process Prediction and Mathematical Programming, Agent Technologies for Energy Systems Workshop (ATES) at AAMAS 2011

Energy Forecast Model

Time Series Regression Model

1- Weather
2- Zones Sensible Cooling Rate

Total Energy Consumption

$$y_t = \sum_{j=0}^{k} \beta_j x_{tj} + \varepsilon_t$$

Can Explain the effects of nonlinearity, missing variables and …

$$\varepsilon_t = \xi(\varepsilon_{t-1}, \ldots, \varepsilon_{t-q}) + \alpha_t,$$

White noise

Error Terms are assumed to follow ARIMA model

$$\phi_p(B)\Phi_P^s(B)\varepsilon_t = \theta_q(B)\Theta_Q^s(B)\alpha_t,$$

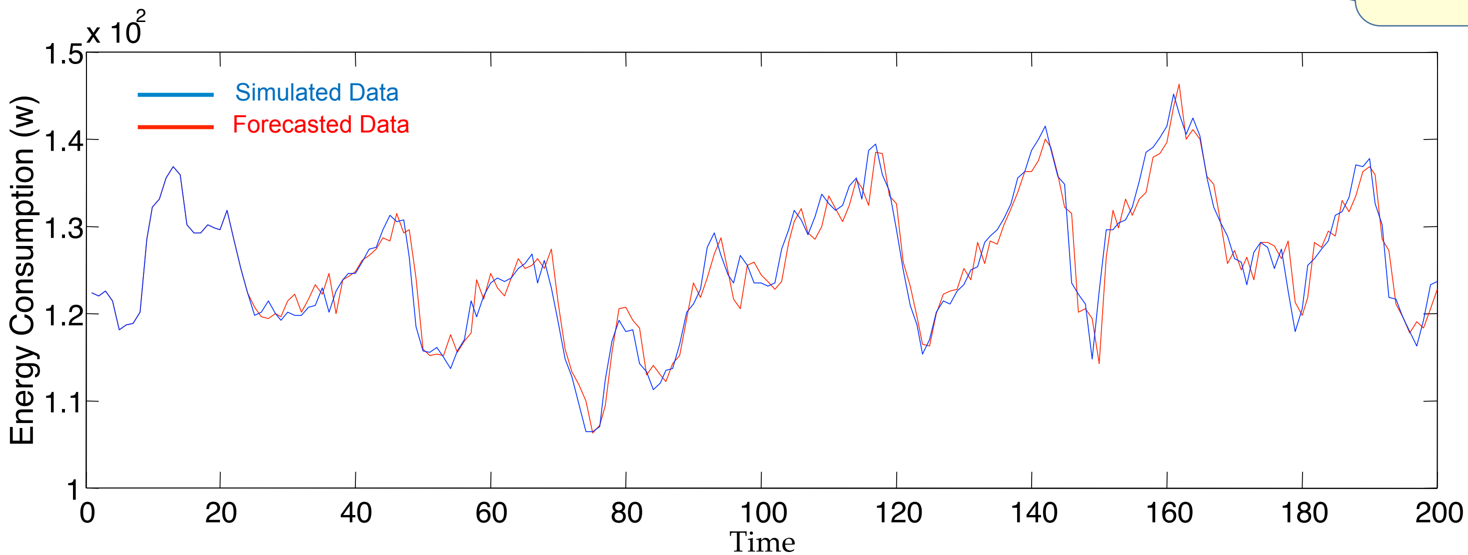
$$y_t = \underbrace{\sum_{j=0}^{k} \beta_j x_{tj}}_{\text{Regression part}} + \underbrace{\varepsilon_t \sum_{i=0}^{p}\sum_{j=0}^{P} (-1)^{i+j-1} \varphi_i \phi_j B^{i+s\times j} + \alpha_t \sum_{i=0}^{q}\sum_{j=0}^{Q} (-1)^{i+j} \theta_i \Theta_j B^{i+s\times j}}_{\text{Time Series part}}$$

How to Estimate Parameters : Cochrane-Orcutt Transformation

Physical-Statistical Model – Energy Forecast Mode

Forecast Model Validation

APEP Bldg.
UCI
2009 August Data



$$R^2 = \frac{\hat{\boldsymbol{\beta}}^T \mathbf{X}^T{}_2 (I - H) \mathbf{X}_2 \hat{\boldsymbol{\beta}}}{\mathbf{y}^T{}_2 (I - H) \mathbf{y}_2}$$

$R^2 = 95.7\%$

$$R^2_{adj} = \frac{\hat{\boldsymbol{\beta}}^T \mathbf{X}^T{}_2 (I - H) \mathbf{X}_2 \hat{\boldsymbol{\beta}} / k - 1}{\mathbf{y}^T{}_2 (I - H) \mathbf{y}_2 / n_2 - k}$$

$R^2_{adj} = 94.3\%$

Physical-Statistical Model – Optimization Model

There are two Objective Functions

$$G_1(.) \equiv \underbrace{\sum_{k=1}^{N-1} c_{t+k}\, y_{t+k}\left(R^{t+k+1}, T_{ext}^{t+j}\right).\Delta t}_{\text{Usage Cost}} + \underbrace{\kappa . \max_{k \in t_d}\left\{ y_{t+k}\left(R^{t+k+1}, T_{ext}^{t+j}\right)\Delta t \right\}}_{\text{Demand Charge Cost}}$$

$$G_2(.) \equiv \underbrace{\sum_{k=1}^{N}\left(p_1\left|\delta_{t+k}^{u}\right| + p_2\left|\delta_{t+k}^{l}\right|\right)}_{\text{Penalty for Exceeding Thermal Comfort Limits}}$$ [1]

temperature violation above the upper / lower bound

Obj. Functions is not necessarily additive

1) Ma, Y.; Kelman, A.; Daly, A.; Borrelli, F.; , "Predictive Control for Energy Efficient Buildings with Thermal Storage: Modeling, Stimulation, and Experiments," Control Systems, IEEE , vol.32, no.1, pp.44-64, Feb. 2012

Physical-Statistical Model – Optimization Model

Constraints

1

$$\hat{T}_{in}^{t+j}(i) = \hat{T}_{in}^{t+j-1}(i) + \hat{\alpha}_i .R^{t+j-1}(i) + \hat{\varphi}_i \left(\hat{T}_{in}^{t+j-1}(i) - \hat{T}_{ext}^{t+j-1}(i)\right)$$

Thermal Balance Eq.

2

$$T_{min}^{t+j}(i) - \left|\delta_{t+k}^{l}\right| \leq \hat{T}_{in}^{t+j}(i) \leq T_{max}^{t+j}(i) + \left|\delta_{t+k}^{u}\right|$$

Thermal Comfort Constraints

$$\delta_{t+k}^{l}, \delta_{t+k}^{u} \geq 0$$

$$i = 1,2,\ldots,m\,(\#\text{ zones}),\ j = 1,2,\ldots,N$$

Physical-Statistical Model – Optimization Model

$$G_1(.) \equiv \min \sum_{k=1}^{N-1} c_{t+k} y_{t+k}\left(R^{t+k+1}, T_{ext}^{t+j}\right).\Delta t + \kappa. \max_{k \in = t_d} \left\{ y_{t+k}\left(R^{t+k+1}, T_{ext}^{t+j}\right)\Delta t \right\}$$

$$G_2(.) \equiv \min p \sum_{k=1}^{N} \left(\left|\delta_{t+k}^{u}\right| + \left|\delta_{t+k}^{l}\right| \right)$$

$S.t.$

$$\begin{cases} \hat{T}_{in}^{t+j}(i) = \hat{T}_{in}^{t+j-1}(i) + \hat{\alpha}_i . R^{t+j-1}(i) + \hat{\varphi}_i \left(\hat{T}_{in}^{t+j-1}(i) - \hat{T}_{ext}^{t+j-1}(i) \right) \\ T_{min}^{t+j}(i) - \left|\delta_{t+k}^{l}\right| \le \hat{T}_{in}^{t+j}(i) \le T_{max}^{t+j}(i) + \left|\delta_{t+k}^{u}\right| \\ \delta_{t+k}^{l}, \delta_{t+k}^{u} \ge 0 \end{cases}$$

$$i = 1,2,\ldots,m \,(\#\ \text{zones}),\ j = 1,2,\ldots,N$$

Dynamic Programming

Neural Network Model

- Non-linear Autoregressive with External Inputs (NARX) Neural Network fits to EnergyPlus simulation data

$$S_{t+1} = f_{NN}(S_t, S_{t-1}, S_{t-2}, \dots, S_{t-d_s}, \\ x_t, x_{t-1}, x_{t-2}, \dots, x_{t-d_x}, \\ u_t, u_{t-1}, u_{t-2}, \dots, u_{t-d_u})$$

S: system states (power, average room temperature)
x: weather and operation factors
(time, month,
dry bulb temp, dew point temp,
lighting load, plug load, occupancy)
u: control inputs (cooling setpoint, heating setpoint)

Neural Network Model – Model Validation

- Model is trained with data generated from 25 year simulation and randomly generated operations and control inputs (to have enough variations)
- NARX with 11 hidden layer nodes and 1 step delay

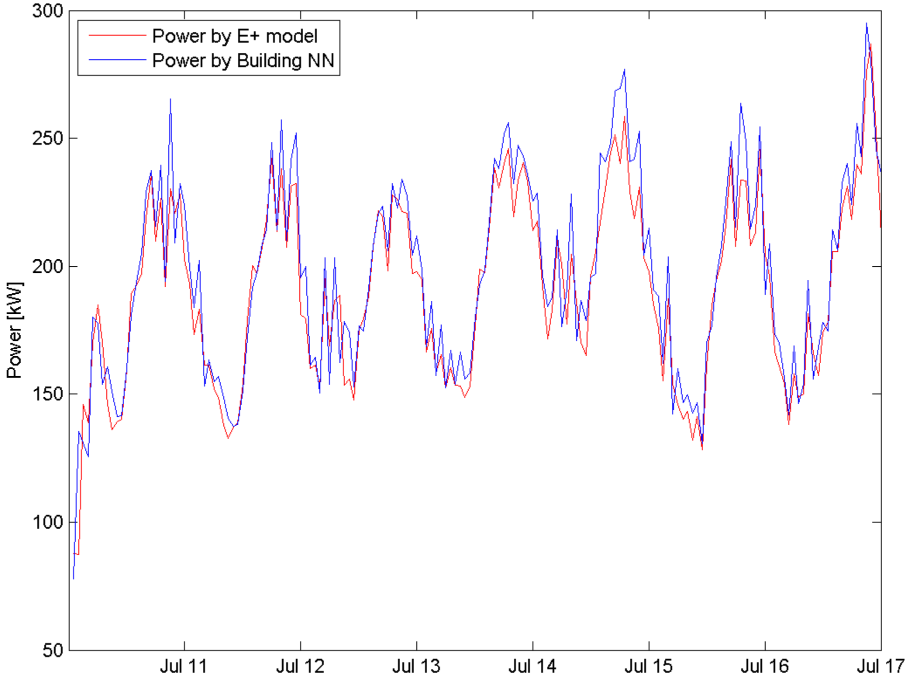
R^2 =0.9979

- Prediction error:

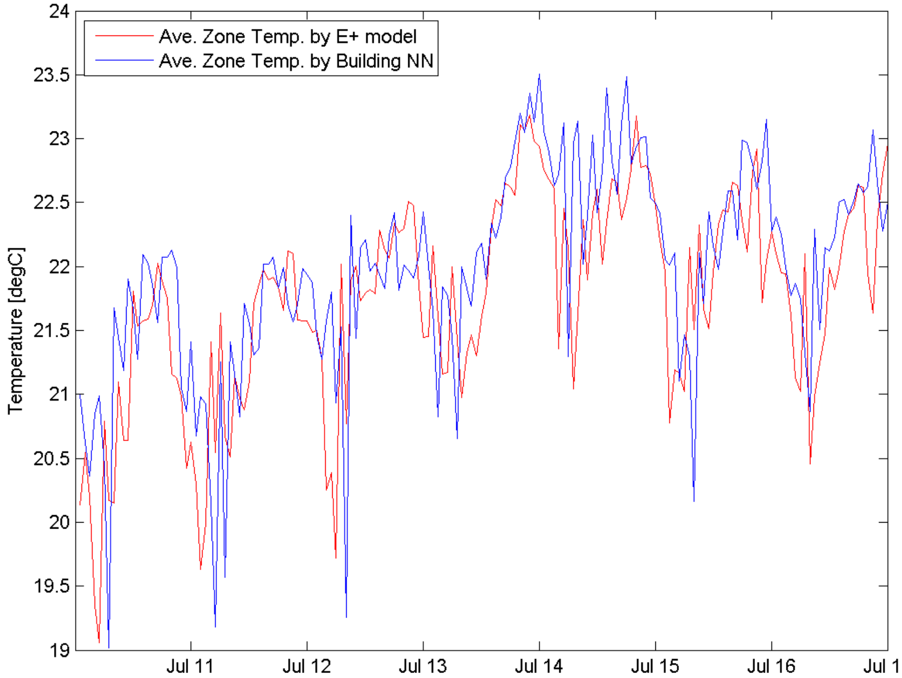
Power: ≈10kW

Ave. Zone Temp: ≈1°C

Power



Avg. Zone Temp



Day-Ahead Planning

- Planning problem formulation

Minimize: $\sum_{t=1}^{24} F_t$

s. t.: $F_t = C_t P_t + \alpha U(T_t)$

$$U(T_t) = (T_t - T_{opt})^2$$

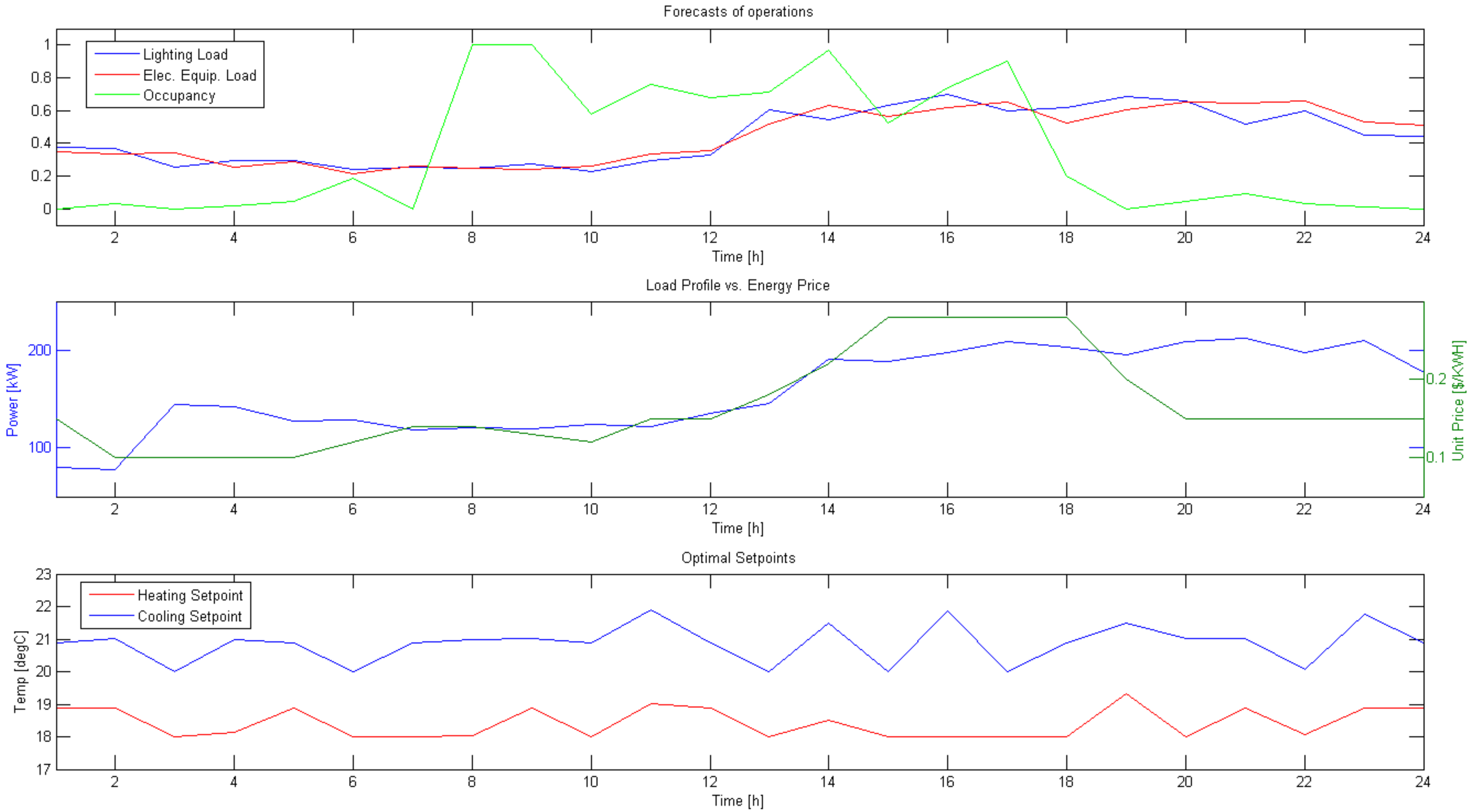
Deviation from optimal (comfortable) temperature

$$\begin{bmatrix} P_t \\ T_t \end{bmatrix} = NARX\_NN(W', O', u')$$

F: overall cost
C: unit price of energy consumption
P: energy consumption
α: thermal comfort loss coefficient
U: thermal comfort loss

T: room temp
T_{opt}: optimal indoor air temp
W': weather forecast
O': operations forecast
u': planned control inputs

Neural Network Model – Day-Ahead Planning result



Real-Time Load Tracking

- Load Tracking problem formulation

$$\text{Minimize: } \sum_{t=1}^{24} D_t$$

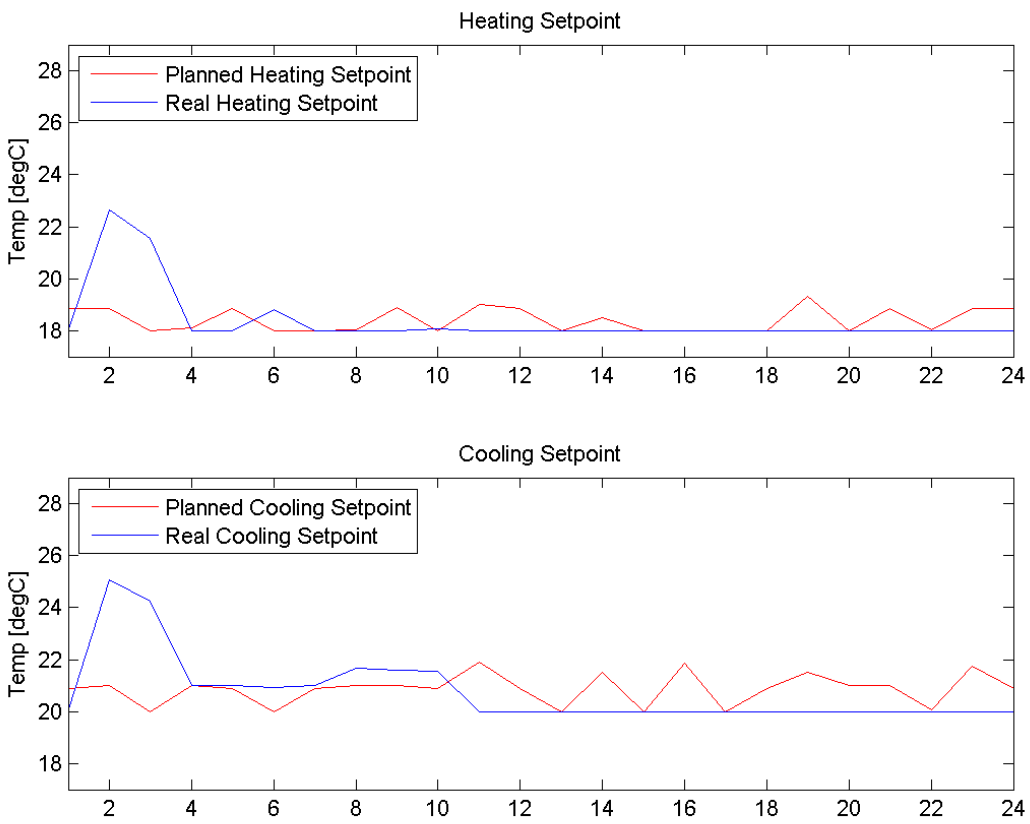
$$\text{s. t.: } D_t = CFD_t(P_t - P'_t)^2$$

$$\begin{bmatrix} P_t \\ T_t \end{bmatrix} = NARX\_NN(W, O, u)$$

D: Contract-for-Difference cost
CFD: Contract-for-Difference rate
P: real energy consumption
P': planned/committed consumption

T: room temp
***W*: real weather**
***O*: real operations**
***u*: real control inputs**

Real-Time Load Control



Tracking load deviation:
<25 KW (12%)

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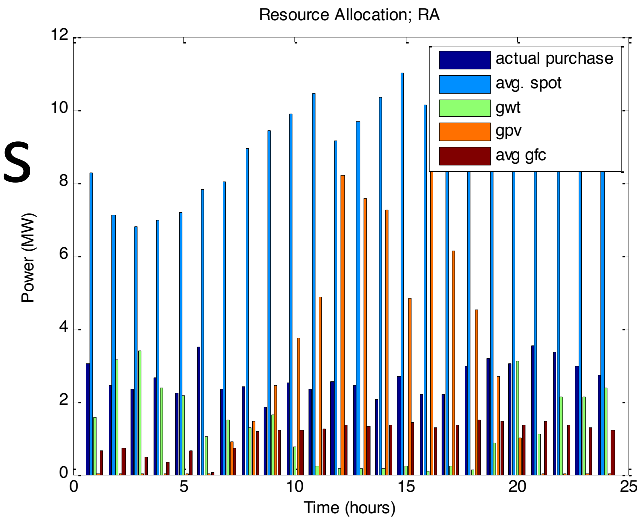
Microgrid Planning and investment
Net Zero communities
AFV fueling infrastructure

Dynamic Pricing and Coordinated Response

- Community/complex level planning and control with base loads, plug-ins (EVs)
- Dynamic Pricing
  - Time-of-Use rate is settled 24-hour ahead by automated negotiation between Energy Management Controller (EMC) and each individual building
    - EMC: determines price based on aggregated load profile (forecast) and whole sale market (forecast)
    - Individual building: load planning based on price
  - Contract-for-Difference (CFD) price is charged to individual buildings, on the difference between real and committed load profiles
    - Individual building: load tracking to minimize CFD charges
    - Coordinated response to minimize CFD charges
- Minimizing demand variations and risks to the grid (distribution)
- Demand Elasticity of use and and its contribution to coordination

Microgrid Planning, control and investment

- Microgrid day-ahead planning and same day control under uncertainty;
- Functional form for MG savings



$$Cost_{MG,t} = f(I_{GF,t}, I_{PV,t}, I_{WT,t}, I_{WT,t})$$

$$I_{GF} = \frac{GFCap}{E[D]}$$

$$I_{PV} = \frac{Average\ Daily\ PV\ Electricity\ Production}{Average\ Daily\ Demand} = \frac{PVCap}{E[D]} = \frac{C_{PV} \times E[SI]}{E[D]}$$

$$I_{WT} = \frac{Average\ Daily\ WT\ Electricity\ Production}{Average\ Daily\ Demand} = \frac{WTCap}{E[D]} = \frac{C_{WT} \times \eta_{WT} \times E[WS^2]}{E[D]}$$

$$I_{ST} = \frac{STCap}{E[D]}$$

Microgrid Planning, control and investment

- Micro-grid power generation portfolio optimization under uncertainty;
  - short-term uncertainties rising from micro-grid operation, and
  - long-term uncertainties due to future natural gas prices, investment in renewable assets, and financing costs.

Microgrid Planning, control and investment

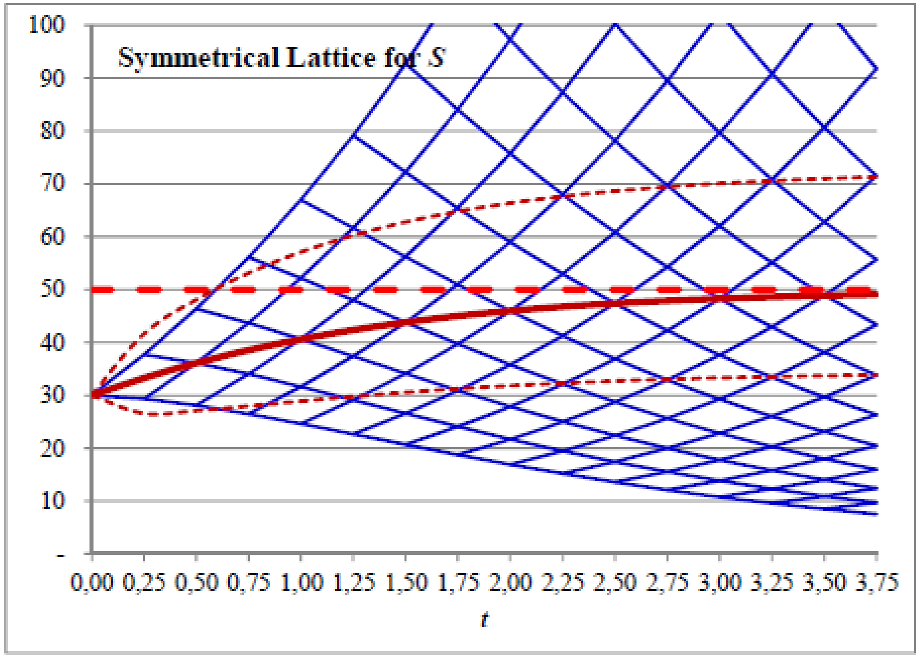
- A solution approach that uniquely combines a general binomial lattice with mixed integer quadratic model for budgeting and a regression model that estimates cost of operation and planning micro-grid with its current resources and load.

$$x'_t = x'_{t-1} + (\alpha_C - \frac{\sigma_C^2}{2})\Delta t$$

$$x'_t = x'_{t-1} + (\alpha_C - \frac{\sigma_C^2}{2})\Delta t$$

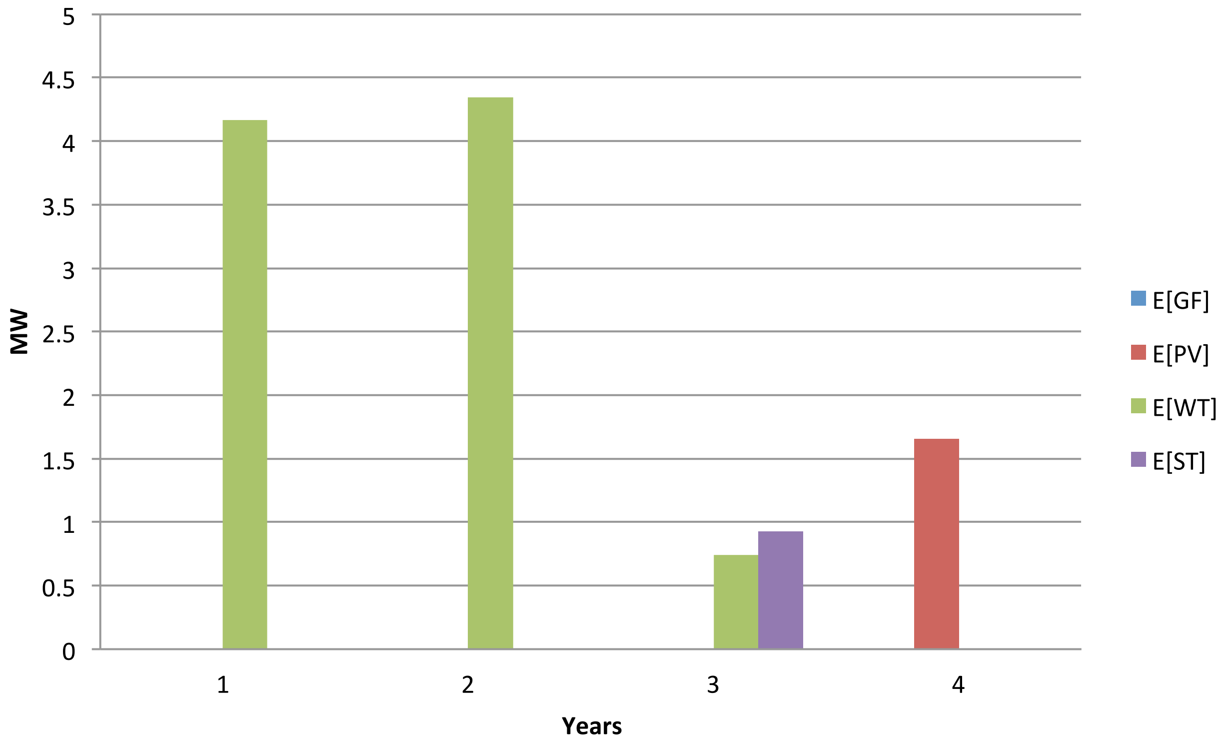
$$dC = \alpha_{N.G.} Cdt + \sigma_{N.G.} CdZ_{N.G.}$$

=



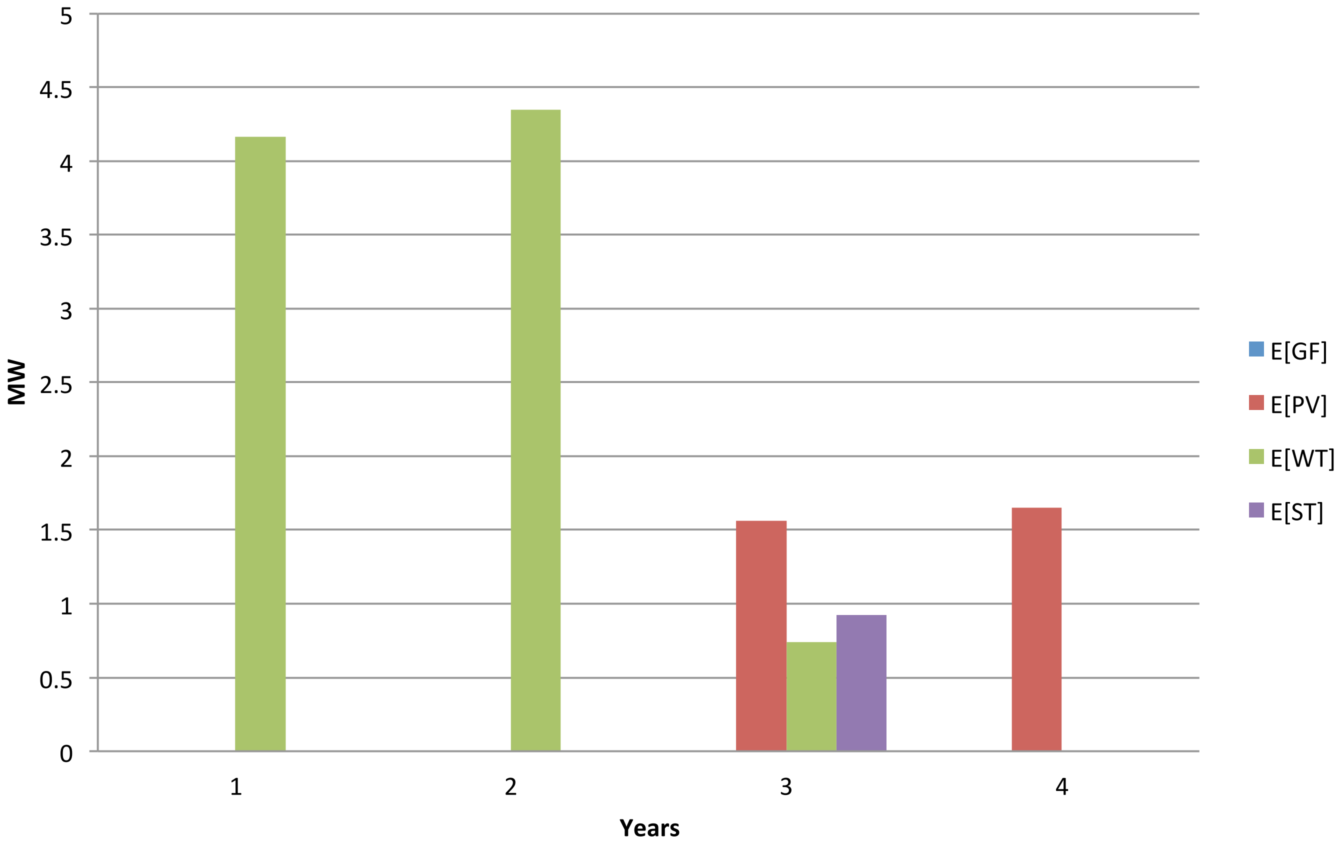
Microgrid Planning, control and investment

$$Cost_{MG,t} = \beta_{0,t} + \beta_{1,t} I_{GF,t} + \beta_{2,t} I_{PV,t} \times I_{WT,t} + \beta_{3,t} I_{WT,t} \times I_{ST,t}$$



Microgrid Planning, control and investment

$$Cost_{MG,t} = \beta_{0,t} + \beta_{1,t} I_{GF,t} \times I_{ST,t} + \beta_{2,t} I_{PV,t} \times I_{WT,t} + \beta_{3,t} I_{PV,t} \times I_{ST,t} + \beta_{4,t} I_{WT,t} \times I_{ST,t}$$



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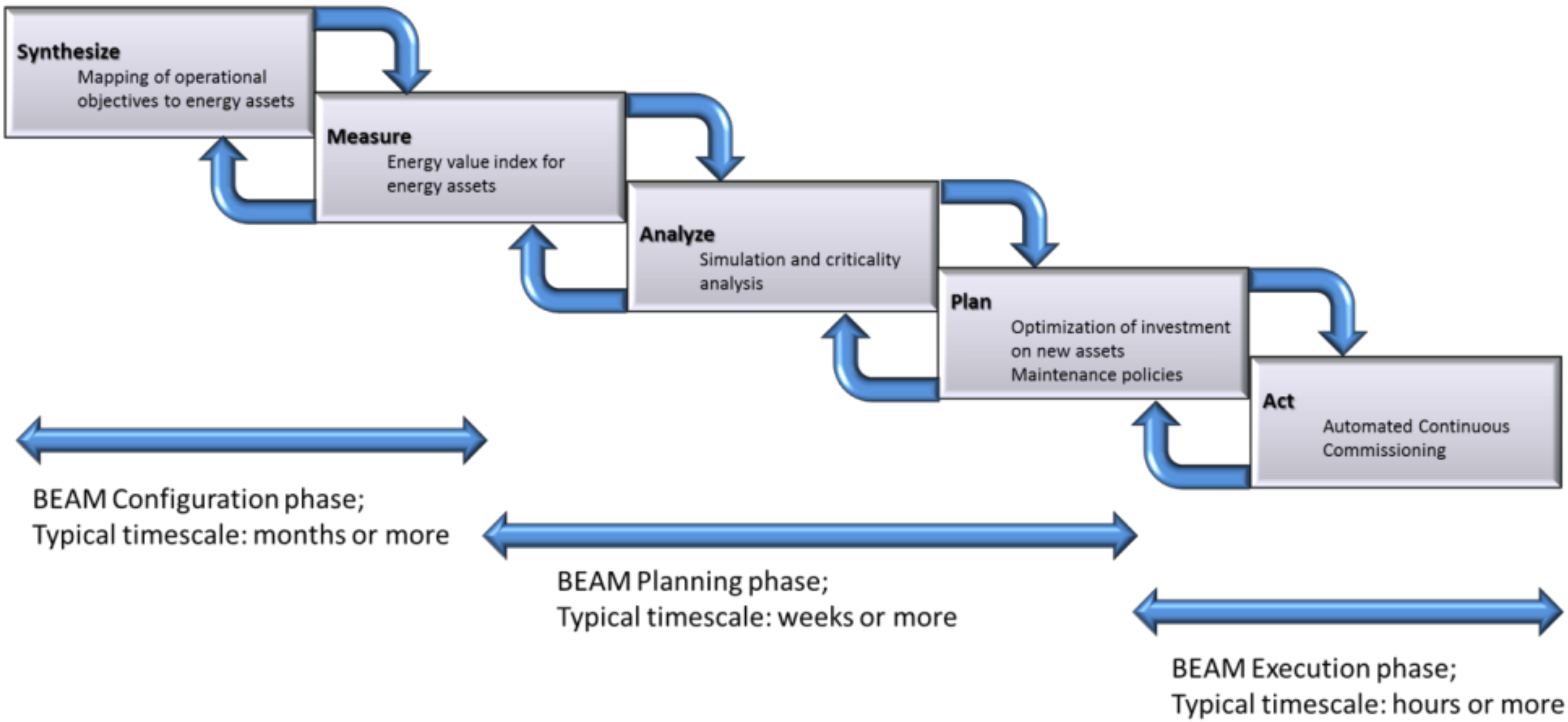
Building Energy Asset Management (BEAM)



Energy-Plus used in operation and long term planning.

BEAM O & M Optimization

Objective #1. Min{Total Building Energy Consumption}

Objective #2. Min{Total Building Cost}

subject to:

Total Building Cost ≤ Total Budget

Mutually Exclusive O &M Policy Options

We will assume that:

Asset energy consumption ~ Asset Avg. effective age

Min {Avg. asset effective age} ≡ Max {Total improvement in asset effective age}

BEAM O & M Optimization

Two Types of Optimization for Building O&M

- **O&M Optimization I:**
  - Only direct impacts of O&M policies

- **O&M Optimization II:**
  - Both direct & indirect impacts of O&M policies

  i.e. maintenance policy put on asset 1, not only improves asset 1's effective age, but it also impacts asset 2's effective age (positive or negative impact).

BEAM O & M Optimization

Objective #1

Min {Total Building Energy Consumption}

~

Max{Total Assets Energy Performance Improvement}

$$= Max \left\{ \sum_{t,i,k,l} \Delta_{tikl} \times x_{tikl} \right\}$$

Optimization I & II differ in Δ_{tikl} Calculation

Where

$$x_{tikl} = \begin{cases} 1 & if\ Policy\ (t;k,l) is\ on\ asset\ i \\ 0 & Otherwise \end{cases}$$

$\forall t = 1,2\ (seasons)$

$\forall i = 1, \dots, n\ (assets)$

$\forall k = 1, \dots, 6\ (maintenance\ policy\ in\ BEAM)$

$\forall l = 1, \dots, m\ (frequency)$

BEAM O & M Optimization

Objective #2

Total Building Cost = $\underbrace{\text{Total Preplanned Action Cost}}_{\text{Fixed maintenance Cost}}$ + $\underbrace{\text{Asset Penalty Cost + Unexpected Reactive Cost}}_{\text{Cost upon asset failure}}$

Total Building Cost = Total Preplanned Action Cost + Asset Penalty Cost$_{\text{BaseOption}}$ - Reduction in Penalty Cost + Unexpected Reactive Cost$_{\text{BaseOption}}$ – Reduction in Unexpected Reactive Cost

Due to reduction in # failures

Reduction in Penalty Cost + Reduction in Unexpected Reactive Cost = Total Reduction in Unexpected Cost

Min {Total Building Cost} = Min {Total Preplanned Action Cost – Total Reduction in Unexpected Cost}

BEAM O & M Optimization

Objective #2

$$Min\{Total\ Building\ Cost\}$$

$$= Min\left\{\sum_{t,i,k,l} \underbrace{(C_{PA_{tikl}}) \times x_{tikl}}_{\text{Total preplanned action cost}} - \underbrace{[(C_{PR_{tikl}}) + (C_{RR_{tikl}})] \times x_{tikl}}_{\text{Total reduction in unexpected cost}}\right\}$$

Where

$$C_{PA} = PrePlanned\ Action\ cost \qquad \forall i, \forall (t;\ k, l)$$
$$C_{RR} = E(Unexpected\ Reactive\ Cost\ Reduction) \qquad \forall i, \forall (t;\ k, l)$$
$$C_{PR} = E(Penalty\ Cost\ Reduction) \qquad \forall i, \forall (t;\ k, l)$$

BEAM O & M Optimization

Constraints

1 $$\sum_{k,l} x_{tikl} \leq 1 \qquad \forall t, i$$

Mutually Exclusive Options

Total building cost ≤ Total budget

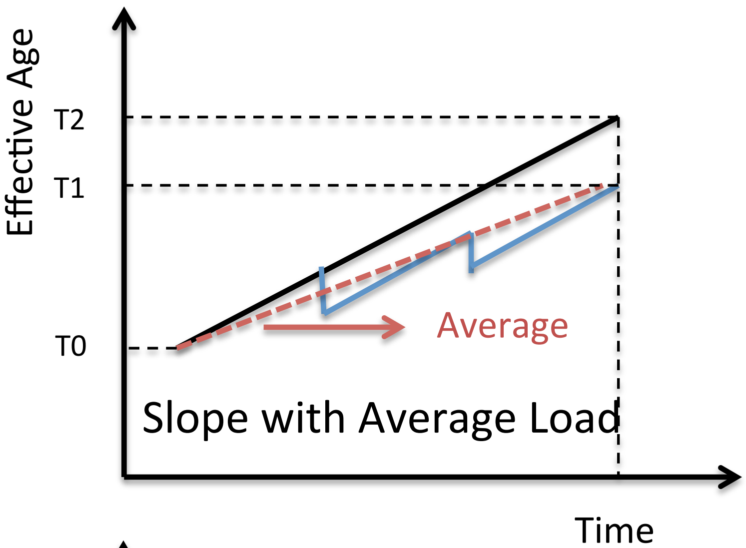
2 $$\sum_{t,i,k,l} [(C_{PA_{tikl}}) - (C_{RR_{tikl}})] \times x_{tikl} \leq B_{limit} - \sum_{t,i} C_{R\_base_{ti}}$$

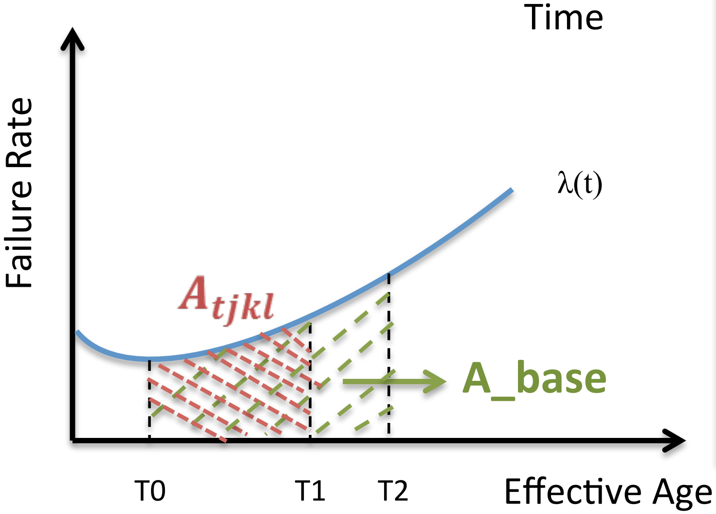
Where

$$C_{PA} = PrePlanned\ Action\ cost \qquad \forall i, \forall (t;\ k, l)$$
$$C_{RR} = E(Unexpected\ reactive\ cost\ reduction) \qquad \forall i, \forall (t;\ k, l)$$
$$C_{R\_base} = E(Unexpected\ reactive\ cost\ of\ base\ option) \qquad \forall t, i$$

BEAM O & M Optimization

Optimization I, Coefficient Calculation: C_{R_base}





$$A_{base} = \int_{T_0}^{T_2} \lambda(t) = E(\#failure\ in\ base\ option)$$

$$A_{tikl} = \int_{T_0}^{T_1} \lambda(t) = E(\#failure\ in\ option\ (t;k,l) for\ i)$$

$$C_{RR_{tikl}} = (A_{base} - A_{tikl}) \times \frac{(C_{repair_i} + C_{replace_i})}{2}$$

Unexpected reactive cost reduction

$$C_{R_{base}} = A_{base} \times \frac{(C_{repair_i} + C_{replace_i})}{2}$$

Unexpected reactive cost of base option

BEAM O & M Optimization

Optimization I, Coefficient Calculation: C_{P_base}

$$C_{PR_{tikl}} = (A_{base} - A_{tikl})$$

$$Penalty\ per\ failure\ of\ asset\ i$$

Penalty cost reduction

$$C_{P_{base}} = (A_{base})$$

$$\times\ Penalty\ per\ failure\ of\ asset\ i$$

Penalty cost base option

Where

$C_{PR_{tikl}} =$

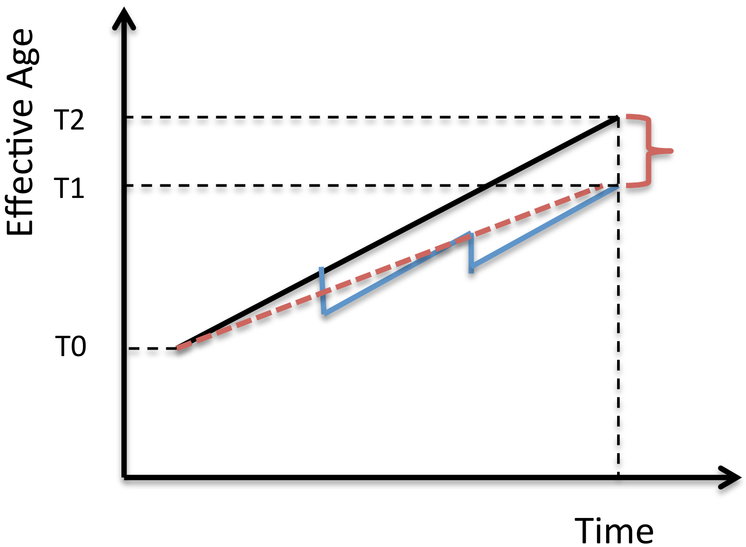
E(Penalty cost reduction for asset i *with option* $(t; k, l)$)

Penalty per failure of asset i can be obtained from BEAM's BVM-II score.

BVM-II (Building Value Model) score is the $ value loss per failure of an asset.

BEAM O & M Optimization

Optimization I, Coefficient Calculation: Δ_{tikl}



$$\forall (t; k, l)$$

$$for\ i = 1, \dots, n \text{ assets}$$

$$\delta^{(t;k,l)} = \begin{bmatrix} \delta_{11} & \dots & \delta_{1n} \\ \delta_{21} & \dots & \delta_{2n} \\ \delta_{n1} & \dots & \delta_{nn} \end{bmatrix}$$

Improvement dependencies matrix

$${\delta_{ii}}^{(t;k,l)}: Improvement\ in\ asset\ i\ as\ a\ result\ of\ (t; k, l)$$

$${\delta_{ij}}^{(t;k,l)}: Improvement\ in\ asset\ j\ as\ a\ result\ of\ (t; k, l)\ on\ asset\ i$$

$$\boldsymbol{{\delta_{ij}}^{(t;k,l)} \cong 0 \quad \forall i \neq j\ (in\ optimization\ I)}$$

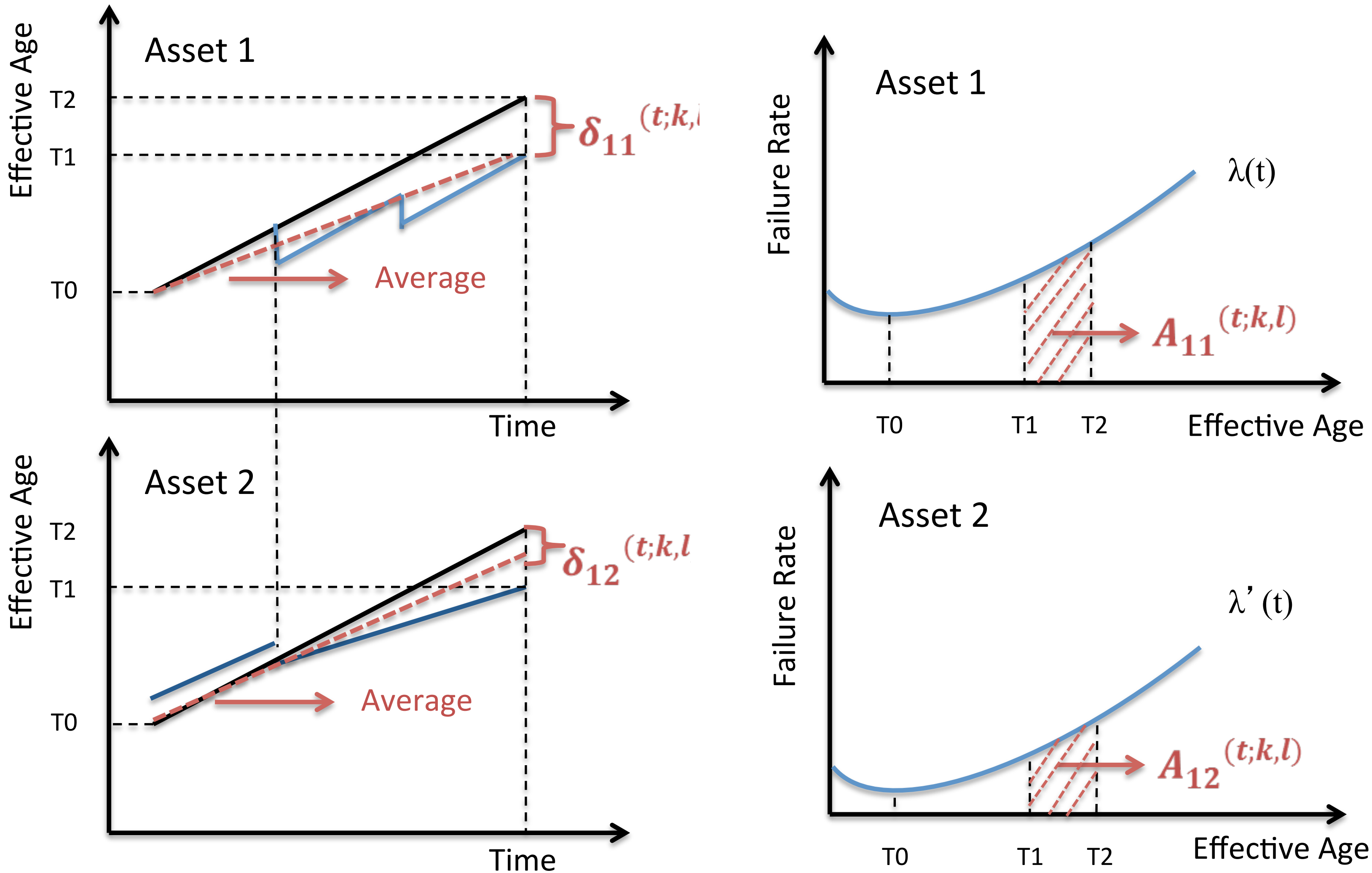
$$\Delta_{tikl} = {\delta_{(i,:)}}^{(t;k,l)} \times (EW)^T \times \ (Avg\ Seasonal\ Degradation)_{\ t,i}$$

Obtained offline from EnergyPlus

$$EW: Energy\ Weight\ Matrix$$

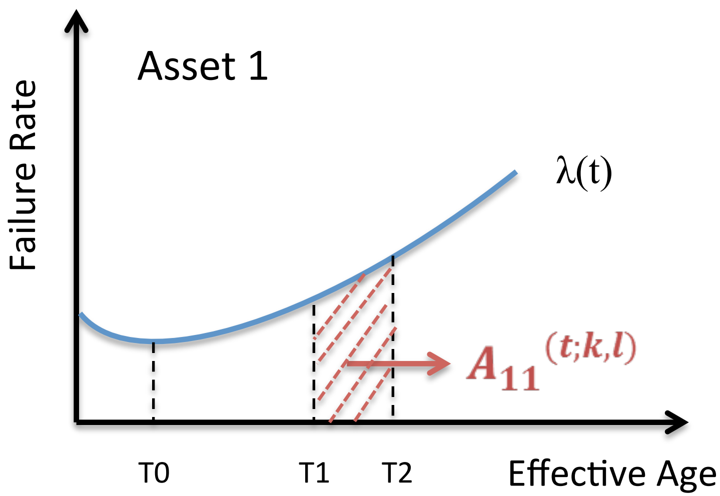
BEAM O & M Optimization

Optimization II-2 asset example option (t;k,l) on asset 1

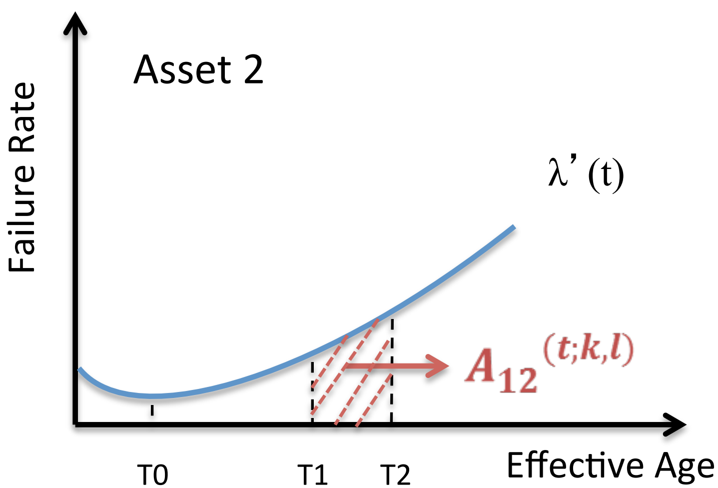


BEAM O & M Optimization

Optimization II - option (t;k,l) on asset 1



$$C_{RR_{t1kl}} = \left[\left(A_{11}{}^{(t;k,l)}\right) \times \left(\frac{C_{repair_1} + C_{replace_1}}{2}\right)\right] + \left[\left(A_{12}{}^{(t;k,l)}\right) \times \left(\frac{C_{repair_2} + C_{replace_2}}{2}\right)\right]$$



Where

$$C_{RR_{t1kl}} = \text{E(Unexpected Reactive Cost Reduction for asset i with option (t; k, l))}$$

BEAM Optimization

- It is highly unlikely that there exists a feasible solution that optimizes all objectives!
- Instead, we seek a small set of feasible solutions which are non-dominated
- Feasible solution is non-dominated if
  - There is no other feasible solution that is better or equal in all objectives

BEAM Optimization – Case Study

- Scenario #1-Optimization only on chiller: Optimal policy for chiller : Preventive Maintenance Clock-based type 3, Frequency=3 months

- Scenario #2-Optimization on 6 assets:

  Recommended Optimal Policy are:

  Chiller: Preventive Maintenance Clock-based type 3, Frequency=3 months

  Boiler: Preventive Maintenance Age-based type 3, Frequency=3 months

  Supply Fan 1 (AHU 1): Preventive Maintenance Clock-based type 3, Frequency=3 months

  Supply Fan 2 (AHU 2): Preventive Maintenance Age-based type 3, Frequency=3 months

  Return fan 1 (AHU 1):Preventive Maintenance Clock-based type 3, Frequency=3 months

  Return fan 2 (AHU 2): Preventive Maintenance Age-based type 3, Frequency=6 months

Energy Savings

(4 year planning)

	Chiller Electricity Consumption	Boiler Gas Consumption	Building Total Electricity Consumption	% Saving in Building Electricity	% Saving in Boiler Gas Consumption
Baseline	1696597.721 KWh	1923835.056 KWh	3588151.297 KWh	-	-
Optimization on Chiller	1565035.065 KWh	1919373.119 KWh	3427283.006 KWh	4.5%	-
Optimization On 6 Assets	1542024.515 KWh	1889991.510 KWh	3395089.094 KWh	5.4%	1.7%*

Energy Savings

10% degradation increase (4 year planning)

	Chiller Electricity Consumption	Boiler Gas Consumption	Building Total Electricity Consumption	% Saving in Building Electricity	% Saving in Boiler Gas Consumption
Baseline	2560093.637 KWh	1933343.918 KWh	4523347.172 Kwh	-	-
Optimization on Chiller	1659577.289 KWh	1934333.240 KWh	3883931.966 KWh	14.13%	-
Optimization On 6 Asset	1610946.879 KWh	1786283.760 KWh	3522506.937 KWh	22.12%	7.6%